Understanding how contact heterogeneity alters epidemic outcomes is central to evidence–based preparedness. Classica
Introduction High–resolution contact studies routinely report heavy–tailed degree distributions with a small fraction of
Motivated by this gap, we address the following research question: **How does introducing degree heterogeneous**
This investigation contributes three insights. (i) The network reproduction number depends linearly on the mean exces
Methodology Network Construction Two static undirected networks of identical order $N = 5{,}000$ were generated using
SEIR Model on Networks Each node can occupy one of four compartments: Susceptible (S), Exposed (E), Infectious (
$E\sigma I$,
$I\gamma R$. Ten randomly chosen nodes were seeded as infectious; all others were susceptible at $t = 0$. The choice maintains identi
Deterministic Threshold Analysis Under homogeneous–mixing the next–generation approach gives $\mathcal{R}_0^{HM} = \beta/\gamma$. For a

Thus the epidemic threshold in terms of β is $\beta_c^{net} = \gamma/q$. Substituting the empirical moments we obtain $\beta_c^{ER} = 0.014$ and
Stochastic Simulation Protocol We used `fastgemf` version 0.4.2 to run exact continuous–time simulations. For each net
Results Analytical Threshold Comparison Table summarises critical ratios. BA heterogeneity lowers β_c by a factor of

[ht] Deterministic epidemic thresholds

Topology	$\langle k \rangle$	$\langle k^2 \rangle$	β_c ($\gamma = 1/7$)
Homogeneous	–	–	0.143
ER	7.98	71.5	0.014
BA	7.99	167.2	0.006

Stochastic Metrics at $\beta = 0.05$ Twenty–run averages are displayed in Table . Degree heterogeneity elevates $I_{\max}$ by 23

[ht] Average epidemic metrics over 20 stochastic realisations ($\beta = 0.05$). Standard deviations in parentheses.

Network	
ER	6
BA	7

Representative average trajectories are plotted in Figure . The BA curve exhibits a steeper ascent and decay, indicative
[http] [width=0.48]results$_a vg_B A.png[width = 0.48] results_a vg_E R.png Average exposed$(E)$and infectious(I)prevalence fo$
Sensitivity to Transmission Rate Increasing β from 0.03 to 0.08 monotonically amplifies peak size and reduces time–to–
Discussion Our findings reinforce and extend prior insights on the pivotal role of degree variance in epidemic propagati
From a methodological standpoint, the contrast between analytic thresholds and stochastic metrics highlights complem
Limitations include the use of synthetic networks without clustering, absence of demographic turnover, and equal per–e
Conclusion Degree heterogeneity profoundly alters SEIR epidemic dynamics. Analytical derivations show that the basic
*References 9

R. Pastor–Satorras and A. Vespignani, "Epidemic spreading in scale–free networks," *Phys. Rev. Lett.*, vol. 86, no. 14, pp. 3
M. Boguñà, R. Pastor–Satorras, and A. Vespignani, "Absence of epidemic threshold in scale–free networks with degree corre
V. M. Eguíluz and K. Klemm, "Epidemic threshold in structured scale–free networks," *Phys. Rev. Lett.*, vol. 89, p. 108701
L. Muchnik, S. Pei, L. Parra, S. Sreenivasan, J. SRedner, and H. Makse, "Origins of power–law degree distribution in the h
H. Kang, M. Sun, Y. Yu, and X. Zhang, "Spreading dynamics of an SEIR model with delay on scale–free networks," *IEEE*

Reproducibility Materials All Python scripts, network files and CSV outputs are available in the accompanying `output`